Do Electric Vehicles Reduce Carbon Emissions? Verification and Evaluation Based on Energy Structure

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Abstract: Confronting the escalating challenges appertaining to global climate change, countries around the world have been rigorously developing strategies to achieve carbon neutrality. The electrification of transportation systems is a feasible way owing to its profound potential to address issues tied to carbon emissions and environmental contamination. This paper verifies the effect of electric vehicles (EV) sales on carbon emissions through panel data models constructed upon the Environmental Kuznets Curve and moderating effect models considering energy structure. Additionally, the carbon reduction effect (CRE) of EV is proposed as a new statistical indicator to evaluate the impact of EV stock share on each country's carbon emissions. Using data from 19 OECD countries during the period of 2010 to 2021, we find that: (1) An inverse relationship exists between EV sales and carbon emissions per capita, with a 1% increase in EV sales per thousand people leading to an approximate 1.2% decrease in carbon emissions per capita. (2) A country's energy structure positively moderates the relationship between EV sales and carbon emissions, with a more sustainable energy structure amplifying the CRE potential. (3) Despite the rising CRE among studied countries, market penetration remains low, indicating a significant opportunity for further carbon reduction.
Keywords: Electric vehicles, Carbon reduction, Energy structure, Moderating effect model, Indicator construction

1. Introduction

1.1. Background

The escalating crisis of global warming presents an imminent and pressing challenge on a global scale. Consequences of the exceedance of critical temperature thresholds, manifested in phenomena such as glacier disintegration and biodiversity loss pose serious risks to ecological integrity [1]. Today, addressing environmental degradation has become a prominent topic on the global agenda [2]. The principal contributor to these alarming conditions is the unchecked proliferation of greenhouse gas emissions since the advent of the Industrial Revolution [3]. Empirical data reveals that atmospheric carbon dioxide concentrations have ascended to their highest point in 23 million years [4]. Furthermore, a general trend of the yearly increasing carbon emissions is accentuated by a remarkable surge of 6% in 2021 compared with that in 2020 [5]. Such a trajectory of excessive carbon emissions undoubtedly exacerbates the severity of global climate change. According to the Intergovernmental Panel on Climate Change (IPCC), the difficulty of limiting the rise of global temperature to a maximum of 1.5°C would be unprecedented, given the current ever-increasing temperatures. Likewise, the World Meteorological Organization (WMO) has forecasted a 50% probability of global temperature increase of at least 1.5°C relative to the pre-industrial levels (1850-1900) by 2026 [6]. Regrettably, global strategies and efforts to mitigate climate change fall short of effectively managing its dramatic impacts [7]. The persistent surge in carbon emissions portends an ever-increasing challenge in curbing the global temperature rise. This trend, if unaltered, will magnify the Herculean task of confronting and addressing the increasingly critical issue of global climate change.

The energy sector, the primary contributor of global carbon emissions, holds significant potential for addressing the aggravating climate crisis. In response, major economies around the globe, contributing approximately 76% of global carbon emissions, have established ambitious carbon neutrality targets [8]. The crux of realizing these carbon neutrality goals lies fundamentally in shifting towards a cleaner, more sustainable energy structure [9]. As revealed in the "2022 World Energy Statistics Review," petroleum has maintained its position as the most extensively consumed global energy source in 2022, constituting 31% of total energy consumption. What trails closely is coal, which contributes a substantial 27% share of global energy consumption. In contrast, natural gas, regarded as a comparatively cleaner energy source, comprises about 25% [10]. These statistics demonstrate that fossil fuels, mainly petroleum and coal, still accounts for nearly 60% of global energy consumption, underscoring the world's persistent dependence on fossil fuels in spite of the burgeoning of cleaner alternatives such as natural gas. This enduring reliance on fossil fuels highlights the substantial potential for further advancement and broader application of cleaner energy sources.

Amidst the rapid advances in global technological sectors, energy demand is steadily rising, particularly within the transportation industry which has seen a considerable urge in energy requirements. Currently, in the transportation sector, petroleum consumption accounts for approximately 60% of total petroleum use, and the direct carbon emissions from fuel combustion contribute to 24% of total emissions [10]. It necessitates a gradual phase-out of conventional vehicles (CV) including those running on gasoline, diesel, kerosene, and fuel oil, to tackle the environmental and climate challenges and to curtail carbon emissions from transportation. Several countries have promulgated specific policies and timelines for discontinuing internal combustion engine vehicles in response to this imperative. For instance, the European Parliament has enacted legislation in 2023 mandating a prohibition on selling all petrol and diesel vehicles by 2035. Similarly, the United States has issued an executive order stipulating that all newly sold light-duty vehicles be zero emissions by 2035. These measures boost the transition towards cleaner and more sustainable modes of transportation.

The growing public cognizance of climate externalities and advancements in low-carbon technologies have compelled governments all over the world to implement policies that foster the development of EV. These include vigorous promotion and incentivization of EV through various measures, such as purchase rebates, tax exemptions, tax credits, and diverse benefits, including access to dedicated bus lanes and exemptions from specific fees (e.g., tolls or parking charges). Notably, at the 2021 United Nations Climate Change Conference convened in Glasgow, several governments and corporations signed a non-binding resolution, colloquially known as the Glasgow Declaration, which seeks to expedite the transition to 100% zero-emission cars and trucks, with the ambitious objective of ensuring tailpipe emissions from all new cars and trucks globally be greenhouse gas-free by 2040. The global trend towards vigorous promotion and steadfast support for the development of EV has contributed to an exponential increase in global sales of such vehicles over the past decade. The market share of EV has consistently grown among all vehicle types [11]. However, the path to the widespread adoption of EV presents disparate challenges among different nations. Specifically, the popularization of four-wheeled electric vehicles poses a challenge in developing countries, while the reverse appears to be the case for two-wheeled electric vehicles [12].

The adoption of EV acts as a catalyst for the transition towards a more sustainable energy structure within the transportation sector, significantly diminishing urban carbon emissions [13]. This transition represents a crucial strategy for nations striving to attain carbon neutrality and confront climate crises [14]. EV provides distinct advantages over their fossil fuel counterparts regarding environmental friendliness and efficiency in that generates minimal direct carbon emissions and pollutants such as PM2.5, SO2, NOx, NH3, and volatile organic compounds, and thus offers significant positive externalities for public health and welfare [15]. China, since 2009, has galvanized efforts to bolster the adoption of EV. Consequently, the advantages of increased emission efficiency resulting from widespread adoption of EV more than compensate for the adverse impact of escalating urban traffic volume [16]. In India, embracing low-carbon transportation modalities has played an indispensable role in mitigating air pollution and aspiring towards carbon neutrality. Predictive models suggest that, by 2070, implementing of net-zero technologies in India's provincial road passenger transport sector could facilitate a reduction in carbon emissions exceeding 80% [17].

Considering the marked role of EV in mitigating carbon emissions and environmental pollution, this study concentrates on exploring the impact of EV advancement on carbon emissions. Furthermore, relevant developmental recommendations are provided to enhance the efficacy of such interventions in achieving carbon neutrality.

1.2. Literature review and hypothesis development

1.2.1 Carbon emissions

Previous research concerning carbon emissions can be divided into two primary categories. The first mainly encompasses studies based on the Environmental Kuznets Curve (EKC) hypothesis. The EKC hypothesis delineates an inverted "U" shaped relation between economic development and environmental quality, suggesting an initial deterioration of various environmental indicators concurrent with economic growth until a certain threshold of per capita income is reached, beyond which improvement ensues [18-20]. Models built upon the EKC hypothesis mostly deploy macro indicators as variables to examine the correlation between economic factors and carbon emissions. While the EKC hypothesis has been queried by many empirical studies [21, 22], it retains its wide application within the domain of environmental research [23]. For example, Li et al., by dissecting per capita carbon emissions from 147 countries worldwide, has discovered that economic growth and structure are the most potent influences respectively on the acceleration and restraining of carbon emissions, and that, conversely, increased renewable energy consumption significantly attenuates carbon emissions per capita [24]. Built upon the EKC hypothesis, Jahanger employs quantile regression with the top 10 nuclear power-generating countries as samples, which unveils the critical role of Information and Communications Technology and nuclear power in enhancing environmental quality [25]. Similarly, Naimoğlu integrates nuclear power, energy prices, and energy imports within the EKC framework and finds that a 1% increase in nuclear power usage and energy prices lead to the respective 0.04% and 0.02% reductions in carbon emissions [26]. Arguably, models based on the EKC hypothesis offer valuable insights into policy orientations related to macroeconomic operation patterns. However, their potential pitfall lies in underestimating the role of technology in policy promotion and the market potential instigated by advancements in energy technology [27].

The second category of research predominantly employs factor decomposition analysis to evaluate the driving forces of carbon emissions. Crucial methodologies within this branch of research of carbon emissions in the transportation sector include the IPAT model, the STIRPAT model built upon the IPAT framework [28], and the LMDI method [29]. The IPAT model divides the impact of human activities (I) into three factors: population (P), affluence (A), and technology (T), and presumes that these factors exert equal influence on carbon emissions. However, the IPAT model has a critical limitation that it fails to encapsulate the non-monotonic and non-linear interrelationships among these factors within its functional formula. Based on the IPAT model, the STIRPAT model has evolved into a stochastic regression impact model designed to decipher the intricate interplay between human social systems and the natural environment. Owing to its non-linear form, the STIRPAT model facilitates the autonomous introduction of multiple variables for parameter estimation [30]. Apart from these two classic models, the LMDI method is also widely used in carbon emissions research. Its fundamental concept is to separate carbon emissions into contributions stemmed from different factors. In existing studies, the LMDI method typically dissects carbon emissions into components such as carbon emissions factors, energy structure, energy intensity, industrial structure, economic scale, population, and so forth [31]. This method features in zero residuals, additivity, broad applicability, and ease of analysis [32]. More importantly, it equips the researchers with a more profound understanding of the determinants of carbon emissions, thereby supplying robust scientific evidence and policy recommendations for carbon emissions mitigation.

1.2.2 EV and carbon emissions

In practice, the life cycle assessment (LCA) method is employed by researchers to gauge the impact of EV on carbon emissions [33]. LCA is leveraged to analyze and appraise the environmental consequences of a product throughout its lifecycle, encompassing stages of production, utilization, and eventual disposal or recycling. Broadly speaking, LCA can be classified into three subsets: process-based LCA, which adopts a "bottom-up" approach [34], economic input-output LCA, which utilizes a "top-down" approach [35], and hybrid LCA, which amalgamates both methodologies [36]. Process-based LCA is an analytical tool that scrutinizes the material and energy flux of individual processes within a system from a micro-perspective, enabling the computation of the product system's carbon footprint [37]. While economic input-output LCA and hybrid LCA contemplate material and energy interactions between sectors from a macro or integrated macro-micro perspective, thereby facilitating the assessment of the carbon footprint of the overall system [38].

Life cycle analyses generally suggest that EV emit less carbon than their conventional fuel counterparts [39]. However, the precise carbon emissions of an electric vehicle throughout its lifecycle are contingent upon various factors including the energy sources leveraged during production and operation [40], user's driving behavior (such as the proportion of time spent driving in electric mode versus gasoline mode in hybrid vehicles) [41], and so on . Further life cycle assessments of EV demonstrate that even in regions with higher Carbon Intensity of Electricity (CIE), EV still emit fewer greenhouse gases than CV [42]. Despite the current reliance of EV on electricity derived from fossil fuel power plants, it is feasible to reduce the overall pollution levels of electric vehicles by transitioning to cleaner sources of electricity [43].

Existing research often analyzes carbon emissions of EV in comparison with CV from a lifecycle perspective. Some of the research focuses solely on the lifecycle carbon emissions of batteries in EV, which, namely, merely considers the lifecycle carbon emissions of EV at a micro level, overlooking their macro-level impacts on the economy, society, and global supply chains [44]. In the context of globalization, the production of EV is concentrated in a handful of countries where the battery manufacturing process, the highest contributor to carbon emissions, is located. As per data from SNE Research, the top three global battery suppliers in 2023, namely CATL, LG, and BYD, are concentrated in East Asia, commanding a combined market share of 64.2%. Such geographical distribution suggests that some of the carbon emissions associated with EV consumption in various consuming countries are transferred to producing countries [45].

Therefore, for most nations, it is more policy-relevant to discuss the impact of the widespread adoption of EV on carbon emissions at the macro level, which at the same time complements existing research focused on lifecycle analysis of carbon emissions from EV. Hence, this study posits the following hypothesis H_1 from a macroeconomic perspective:

H_1: The impact of EV sales on the carbon emissions per capita of OECD counties negatively.

1.2.3 Moderating effect of energy structure

Due to the wide assortment of the source of electricity used to charge EV across regions, the energy structure of these different areas significantly influences the carbon emissions stemming from electricity generation. The energy structure refers to the makeup and proportion of various energy sources in a country or region's total energy production or consumption. These energy sources can be divided into clean and non-clean energy according to their environmental impact. Broadly speaking, clean energy includes renewable sources that generate minimal pollution, such as hydroelectric, biomass, solar, wind, geothermal, and marine energy. Specific mineral resources with a relatively low environmental impact, like natural gas, clean coal, and nuclear energy, are also considered clean energy [46, 47]. The higher the proportion of clean energy consumed in a country's total energy consumption, the lower the carbon emissions and vice versa [48]. For example, the average emissions from combined-cycle natural gas power plants typically range from 0.350 to 0.400 kilogram carbon dioxide per kilowatt hour (kg-CO_2/kWh); in contrast, emissions from coal power plants range from 0.750 to 1.050 kg-CO_2/kWh. The average carbon emissions from other renewable energy generation methods are below 0.100 kg-CO_2/kWh [49]. Therefore, the energy structure of a country or region plays a pivotal role in determining the overall carbon emissions resulting from the use of EV and it is crucial to consider this factor when evaluating the environmental impact of the shift towards EV in any given area.

Indicators that measure the cleanliness of an energy structure can be classified into two categories: direct and indirect. Direct indicators demonstrate the share of clean energy consumption concerning the total energy consumption of a country, which is often presented as a relative energy consumption index. This kind of indicator provides a straightforward and immediate understanding of the cleanliness level of a particular energy structure for it directly compares the amount of clean energy consumed with the total energy consumed, offering an unambiguous reflection of the clean energy usage in a particular country. On the other hand, Indirect indicators focus on the carbon dioxide emissions generated by energy consumption, which use emission-related indicators to measure the cleanliness level of an energy structure. Examples of such indicators include carbon emissions efficiency and electricity carbon emission intensity. Carbon emissions efficiency measures how much carbon dioxide is emitted per unit of energy consumed or economic output generated. A higher carbon emissions efficiency indicates a cleaner energy structure, signaling less carbon dioxide is emitted for the same amount of energy or economic output [50]. CIE measures the amount of carbon dioxide emitted per unit of electricity generated, and lower values of this indicator signify a cleaner energy structure [51]. Both direct and indirect indicators provide valuable information about the cleanliness of an energy structure and could be used to guide policies and measures aimed to reduce carbon emissions and promote cleaner energy structures.

The energy structure of a country has a significant impact on the carbon emissions from electricity generation. In 2021, countries like Switzerland, Sweden, Norway, and France boasted clean energy production exceeding 90% of their total energy generation while nations such as Singapore, Israel, Egypt, and South Africa reported less than 10% clean energy generation within the same period [10]. This disparity has resulted in marked variations in the CIE across different countries. For instance, 2021, France reported a CIE of a mere 0.067 kg-CO_2/kWh, while Singapore's CIE was significantly higher at 0.489 kg-CO_2/kWh. Notably, the carbon emissions from a single unit of electricity consumed in an electric vehicle in France are merely 13.7% of those in Singapore. Therefore, the energy composition of a country plays an indisputably significant role in influencing the carbon footprint of EV. It is evident that the energy structure has a moderating effect, whereby a cleaner energy structure can enhance the carbon reduction effect (CRE) of EV. Correspondently, the following hypothesis H_2 is proposed:

H_2: Assuming the invariance of other conditions, a cleaner energy structure for a country will strengthen the negative correlation between EV sales and per capita carbon emissions.

1.3. Research framework

The contributions of this paper are two folds. First, the panel data models and moderating effect models are constructed to test two hypotheses mentioned above. The results demonstrate that the upsurge in EV sales corresponds with a reduction in per capita carbon emissions, and a cleaner energy structure can significantly magnify carbon reduction capabilities of EV. Second, an innovative statistical evaluation indicator is proposed to assess the impact of EV on carbon reduction across different nations. Preliminary findings utilizing this indicator suggest that the market penetration of EV remains relatively low in most countries, thereby revealing a considerable potential for further carbon reduction through the expansion of EV usage.

The subsequent arrangement of this paper is as follows: Section 2 offers a concise overview of the data employed in this study. Section 3 introduces the construction of econometric models to test the previously mentioned hypotheses. Section 4 is dedicated to the development of a statistical evaluation indicator designed to quantify the CRE of EV across various countries. Section 5 presents the concluding remarks of the study.

2. Data

Considering the constraints of data availability, we utilize unbalanced panel data originating from 19 countries within the OECD. The countries involved are Australia, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Italy, Japan, Netherlands, Norway, Portugal, South Korea, Spain, Sweden, Switzerland, the United Kingdom, and the United States. Due to missing values in VMT, a time series model is applied for accurate forecasting. Consequently, the timeframe of VMT spans from 2000 to 2021 and that of the remaining variables is from 2010 to 2021. The definitions and measurement methods of the data is depicted in Table 1, and the data summary is in Table 2.

Table 1

The definitions and measurement methods for variables.

Variables	Symbol	Measuring method	Data source
Carbon Dioxide Emissions Per Capita	CO2	Carbon dioxide emissions are those produced from the burning of fossil fuels and the production of cement. They comprise carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring. CO2 is Carbon dioxide emissions divided by the population size of the corresponding year.	OECD Statistics
EV Sales Per Capita	EVS	EV sales per capita equal to battery EV sales along with hybrid EV sales divided by the population size of the corresponding year.	IEA
Economic Growth	GDP	GDP per capita is gross domestic product, in constant 2015 USD, divided by the population size of the corresponding year.	IMF
Energy Structure	CIE	Carbon intensity is measured in grams of carbon dioxide-equivalents emitted per kilowatt-hour of electricity [52].	Our World in Data
EV Stock Per Capita	STO	EV stock per capita equal to battery EV stock along with hybrid EV stock divided by the population size of the corresponding year.	IEA
Population	POP	Population size, or say, number of the total population.	United Nations
Road Passenger transport	VMT	Number of vehicle miles traveled on all roads across the country.	OECD Statistics

Table 2

Data description.

Variables	Unit	Mean	Standard Error	Median	Minimum	Maximum	Number of Obs.
CO2	Metric tones	8.81	0.27	8.27	3.82	18.06	222
EVS	10^3 Cars	36.32	5.80	8.07	0.00	690.00	222
GDP	10^3 US Dollar	48.01	1.21	46.48	17.92	102.91	222
CIE	kg-CO_2/kWh	0.31	0.01	0.32	0.03	0.67	222
STO	10^3 Cars	83.04	13.31	15.84	0.00	1320	210
POP	10^6 People	51.74	4.91	24.79	4.89	337.00	222
VMT	10^9 Miles	629.35	61.90	264.28	34.46	5954.24	351

To mitigate the issue of heteroscedasticity, the natural logarithm is applied to all variables except for CIE. These transformed variables are designated as LnCO2, LnEVS, LnGDP, and LnSTO. The Pearson correlation matrix of all the variables is presented in Table 3. A negative correlation exists between LnCO2 and LnEVS, as well as LnSTO (with Pearson correlation coefficients of -0.141 and -0.121, respectively). In contrast, LnCO2 exhibits a positive correlation with LnGDP and CIE (with Pearson correlation coefficients of 0.202 and 0.474 respectively), which suggests that an overall increase in GDP tends to escalate CO2, with CIE exerting a more direct impact on CO2. Simultaneously, it can be observed that a positive correlation exists between LnEVS and LnGDP (with a Pearson correlation coefficient of 0.325), implying a tendency towards the acquisition of EV among high-income countries. VMT displays a positive correlation with LnCO2 (with a Pearson correlation coefficient of 0.405), indicating significant potential for carbon emission reduction in the transportation sector across nations. Regarding the econometric models delineated in Section 3, multicollinearity issues are negligible, given the absence of a strong correlation among the primary variables. Given that the dataset is short panel data, wherein the cross-sectional dimension outweighs the time dimension, short non-stationary panel data may lead to biased standard errors. But the point estimations of the value of parameters are consistent, so that there is no need for unit root tests and cointegration tests [53].

Table 3

Results of Pearson correlation matrix.

Variables	LnCO2	LnEVS	LnGDP	CIE	LnSTO	VMT
LnCO2	1.000					
LnEVS	-0.141	1.000				
LnGDP	0.202	0.325	1.000			
CIE	0.474	-0.362	-0.371	1.000		
LnSTO	-0.121	0.592	0.331	-0.354	1.000	
VMT	0.405	-0.113	0.114	0.222	0.018	1.000

3. Methodology

In this section, we will develop econometric models one by one to scrutinize the two hypotheses stated earlier. More specifically, Subsection 3.1 entails the construction of a panel data model for verifying of H_1, whereas Subsection 3.2 presents a model to evaluate the moderating effects in H_2.

3.1. Panel data model

3.1.1 Both time and individual fixed effects

In this part, a panel data regression model is built to validate H_1. The modeling of panel data typically employs a fixed effects model [54]. Given that the individual fixed effects model presupposes equality across all periods in terms of time effect, it can rectify issues related to omitted variables, which are consequences of individual differences that remain constant over time. Concurrently, due to the dramatic changes in the macroeconomic environment over time, some variables that remain the same with individual changes but vary over time might be omitted. As a result, the assumption of equal time effect in each period in the individual fixed effects model does not hold, warranting the incorporation of time-representative dummy variables in the equation, leading to the individual and time two-way fixed effects model.

Fig. 1 depicts a scatter plot between LnEVS and lnCO2 across six countries with varying levels of CO2, and the timeline encompasses the period from 2010 to 2021. The United States and Australia are characterized by high emissions among the OECD countries, and the Netherlands and Germany exhibit average carbon emissions. At the same time, France and Sweden are categorized as low emissions countries. The diverse carbon emissions scenarios across different nations, in which a handful of countries have LnCO2 significantly surpassing the mean value, highlight the necessity to account for individual differences across countries during model development. Meanwhile, an observable downward trend in LnCO2 with increased LnEVS presence is evident across all nations. Additionally, a certain non-linear relationship is discernible between LnEVS and LnCO2, potentially attributable to the scale effect inherent in the development of the EV. In other words, the larger the fleet of EV, the more substantial their impact on carbon emissions. Consequently, the quadratic term of LnEVS should be considered when developing the model.

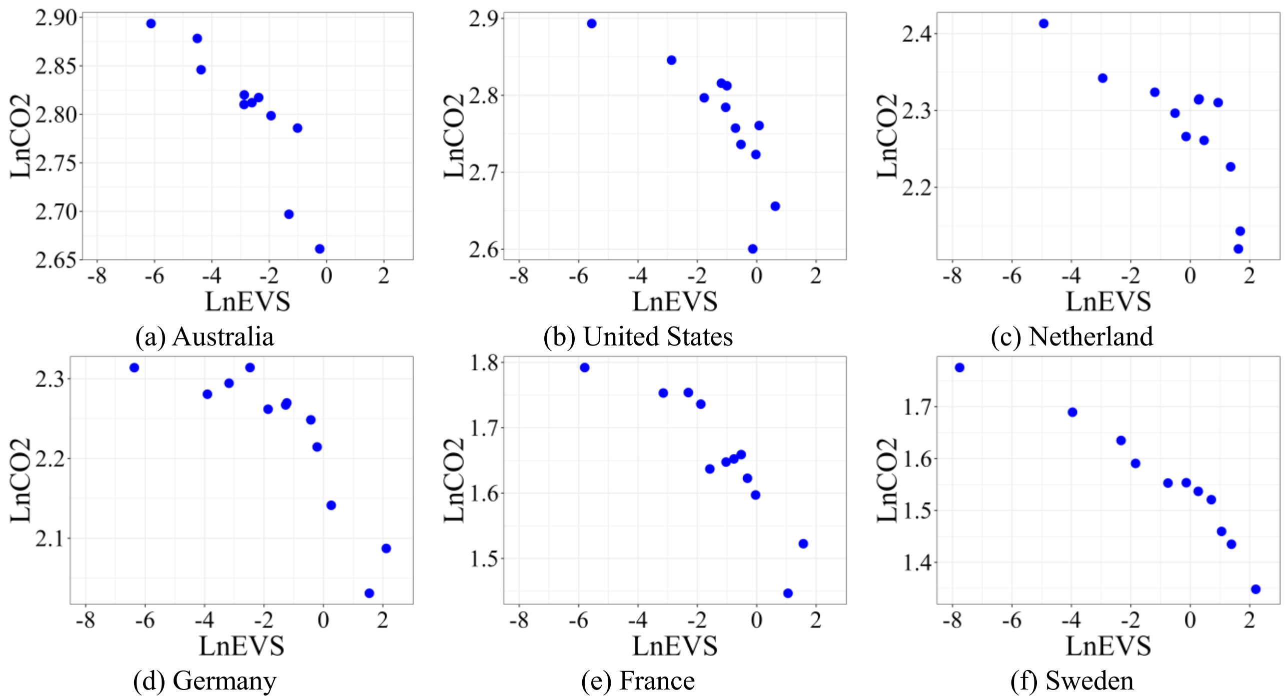


Fig. 1. Scatter plots between LnEVS and LnCO2.

To test Hypothesis H_1, an econometric model is built within the framework of a panel regression model, considering CO2 as the dependent variable and EV sales as the independent variable. Adhering to the Environmental Kuznets Curve, GDP and its squared term are regarded as control variables [55], which is illustrated in Model (1):

$$LnCO2_{it} = \beta_0 + \beta_1 LnEVS_{it} + \beta_2 (LnEVS_{it})^2 + \beta_3 LnGDP_{it} + \beta_4 (LnGDP_{it})^2 + \mu_i + \lambda_t + \varepsilon_{it}, \quad (1)$$

where $i = 1, \cdots, 19$ represents country and $t = 1, \cdots, 11$ represents year. $LnCO2_{it}$ represents the dependent variable. $LnEVS_{it}$ and $(LnEVS_{it})^2$ are the independent variable and its quadratic term. $LnGDP_{it}$ and $(LnGDP_{it})^2$ serve as control variables. $\beta_0, \beta_1, \cdots, \beta_4$ depict regression coefficients, ε_{it} is random error term, μ_i is the intercept term for the heterogeneity of the i-th individual, and λ_t is the time effect for the t-th year. To circumvent the dummy variable trap, we set $\mu_1 = 0$. Notably, Model (1) encompasses several potential relationships between CO2 and EVS: If $\beta_1 > 0$ and $\beta_2 < 0$, an inverted "U" relationship is observed; if $\beta_1 < 0$ and $\beta_2 > 0$, a "U" relationship exists; if $\beta_1 < 0$ and $\beta_2 < 0$, a negative correlation is apparent; if $\beta_1 > 0$ and $\beta_2 > 0$, a positive correlation emerges; and if $\beta_2 = 0$, Model (1) degenerates into Model (2):

$$LnCO2_{it} = \beta_0 + \beta_1 LnEVS_{it} + \beta_3 LnGDP_{it} + \beta_4 (LnGDP_{it})^2 + \mu_i + \lambda_t + \varepsilon_{it}, \quad (2)$$

which indicates a linear relationship.

Table 4

The results of the relationship between EVS and CO2.

Variable	Model (1)	Model (2)
	$LnCO2_{it}$	$LnCO2_{it}$
$LnEVS_{it}$	-0.031***	-0.012**
	(0.007)	(0.006)
$(LnEVS_{it})^2$	-0.003***	/
	(0.001)	
$LnGDP_{it}$	5.211***	4.109***
	(1.250)	(1.251)
$(LnGDP_{it})^2$	-0.238***	-0.186***
	(0.058)	(0.058)
Constant	-25.701***	-19.839***
	(6.751)	(6.763)
Country FE	Yes	Yes
Year FE	Yes	Yes
Number of Obs.	222	222
Adj R^2	0.986	0.985

Note: ***, ** and * represent significance level of 1%, 5% and 10%, respectively. Standard deviations are in parentheses. Same apply to the following tables.

Table 4 presents the estimated results of the models above. The influence of LnEVS on LnCO2 is significant, suggesting that an increase in EVS can mitigate carbon emissions, thereby providing initial validation for Hypothesis H_1. Simultaneously, adding the quadratic term of LnEVS results in a significantly negative coefficient and an elevated adjusted R-square of the model. This suggests that Model (1), positing a non-linear relationship between EV and carbon emissions, is more suitable. It is noteworthy that $\beta_1 < 0$ and $\beta_2 < 0$, implying a monotonically decreasing quadratic function relationship. Model (2) shows that if merely the linear effect of LnEVS on CO2 is considered, it can be found that a 1% increase in EVS will lead to a 1.2% decrease in CO2. Additionally, $\beta_3 > 0$, $\beta_4 < 0$ in Model (1) and $\beta_2 > 0$, $\beta_3 < 0$ in Model (2), which verifies that EKC hypothesis holds in OECD countries. CO2 increase firstly and then decrease with the growth of GDP, which is of some significance for OECD countries to reach carbon neutrality.

Table 5

Results of two-stage least squares.

Variable	First Stage	Second Stage
	$LnEVS_{it}$	$LnCO2_{it}$
$LnEVS_{it}$	/	-0.017* (0.009)
$LnEVS_{i,t-1}$	0.541*** (0.051)	/
$LnGDP_{it}$	18.547 (11.672)	3.392*** (1.143)
$(LnGDP_{it})^2$	-0.810 (0.538)	-0.152*** (0.053)
Constant	-107.439 (63.538)	-16.219 (6.235)
Country FE	Yes	Yes
Year FE	Yes	Yes
Number of Obs.	203	203
Adj R^2	0.943	0.988

3.1.2 Endogeneity and robustness

Within econometric models, endogeneity issues could compromise the precision of regression outcomes. From the standpoint of endogeneity origins, the data on EVS could give rise to measurement errors due to statistical issues, subsequently leading to endogeneity problems. To mitigate this issue, we employ panel instrumental variable methods. Specifically, the lagged EVS is regarded as an instrumental variable for two-stage least squares regression. As detailed in Table 5, the first stage of the regression utilizes the lagged value of LnEVS to anticipate the current value, while the second stage applies the predicted values for regression. The results affirm that the rise in EVS continues to diminish CO2 significantly, substantiating the robustness of empirical outcomes. However, a specific elevation in the regression coefficient for LnEVS in Table 5 might indicate that endogeneity problems could be underestimating the impact of LnEVS on CO2.

Aside from endogeneity issues, another focal point is the robustness of estimation results. Robustness tests often involve swapping core explanatory variables to examine the sensitivity of results to variable selection. In Models (1) and (2), we supplant the logarithm of sales volume LnEVS with the logarithm of electric vehicle stock LnSTO, thus creating the regression Models (I) and (II). The utilization of LnSTO as an alternate variable stem from its strong correlation with LnEVS (See Table 3). Nonetheless, differences in data collection methods between the two can result in variations in sample size compared to the regression Models (1) and (2). The outcomes are depicted in Table 6. All the replaced core explanatory variables are significant at a 1% level. Simultaneously, the signs of replaced explanatory variables align with those in the prior models, indicating the robustness of the empirical results.

Table 6

Results with replacement variables.

Variable	Model (I)	Model (II)
	$LnCO2_{it}$	$LnCO2_{it}$
$LnSTO_{it}$	-0.030*** (0.008)	-0.019*** (0.006)
$(LnSTO_{it})^2$	-0.002** (0.001)	/
$LnGDP_{it}$	1.646 (1.434)	0.371 (1.292)
$(LnGDP_{it})^2$	-0.079 (0.066)	-0.021 (0.059)
Constant	-5.933 (7.863)	1.270 (7.077)
Country FE	Yes	Yes
Year FE	Yes	Yes
Number of Obs.	210	210
Adj R^2	0.986	0.986

Furthermore, benchmark regression Models (1) and (2), grounded on the EKC hypothesis, assess the influence of EVS on CO2, treating LnGDP and its square term as control variables. However, neglecting the EKC hypothesis might make the core explanatory variable insignificant or the effect altered, leading to non-robust regression results, which leads to another robustness testing approach: removing the square term of LnGDP to establish regression Models (III) and (IV) while solely considering the linear influence of economic development levels. The estimation results are shown in Table 7. Findings reveal that, even without the EKC hypothesis, the core explanatory variables are significant at 1% and 5% levels, respectively, with their signs corresponding to the estimation results in Models (1) and (2). This confirms the robustness of the empirical results above. Notably, if we only consider the linear effect of economic development on carbon emissions, the coefficient in front of LnGDP is insignificant, and the sign is positive, reinforcing the validity of the EKC hypothesis.

Table 7

Results of changing control variables.

Variable	Model (III)	Model (IV)
	$LnCO2_{it}$	$LnCO2_{it}$
$LnEVS_{it}$	-0.023***	-0.013***
	(0.007)	(0.005)
$(LnEVS_{it})^2$	-0.002**	/
	(0.001)	
$LnGDP_{it}$	0.090	0.096
	(0.058)	(0.058)
Constant	-1.859***	1.816***
	(0.639)	(0.644)
Country FE	Yes	Yes
Year FE	Yes	Yes
Number of Obs.	222	222
Adj R^2	0.984	0.984

3.2 Moderating effect model

The preceding analysis has demonstrated that the promotion of EVS contributes to a reduction in CO2, thereby supporting Hypothesis H_1. In this segment, we seek to investigate Hypothesis H_2, which posits the moderating effect of energy structure on the relationship between EVS and CO2. First, we enhance the foundation of Models (1) and (2) by introducing additional variables and incorporating the interaction term between the CIE and EVS, thereby constructing a model to elucidate the moderating effect. To mitigate multicollinearity and bolster the interpretability of regression coefficients, it is necessary to centralize variables before testing the moderating effect. We approach this by considering panel data as cross-sectional data and adjusting each variable by subtracting its respective mean value, as expressed in Models (3) and (4).

$$LnCO2_{it} = \beta_0 + \beta_1 \widetilde{LnEVS}_{it} + \beta_2 \left(\widetilde{LnEVS}_{it}\right)^2 + \beta_3 \widetilde{CIE}_{it} + \beta_4 \widetilde{CIE}_{it}\widetilde{LnEVS}_{it} + \beta_5 \widetilde{CIE}_{it}\left(\widetilde{LnEVS}_{it}\right)^2 + \beta_6 LnGDP_{it} + \beta_7 (LnGDP_{it})^2 + \mu_i + \lambda_t + \varepsilon_{it}, \quad (3)$$

$$LnCO2_{it} = \beta_0 + \beta_1 \widetilde{LnEVS}_{it} + \beta_3 \widetilde{CIE}_{it} + \beta_4 \widetilde{CIE}_{it}\widetilde{LnEV}_{it} + \beta_6 LnGDP_{it} + \beta_7 (LnGDP_{it})^2 + \mu_i + \lambda_t + \varepsilon_{it}, \quad (4)$$

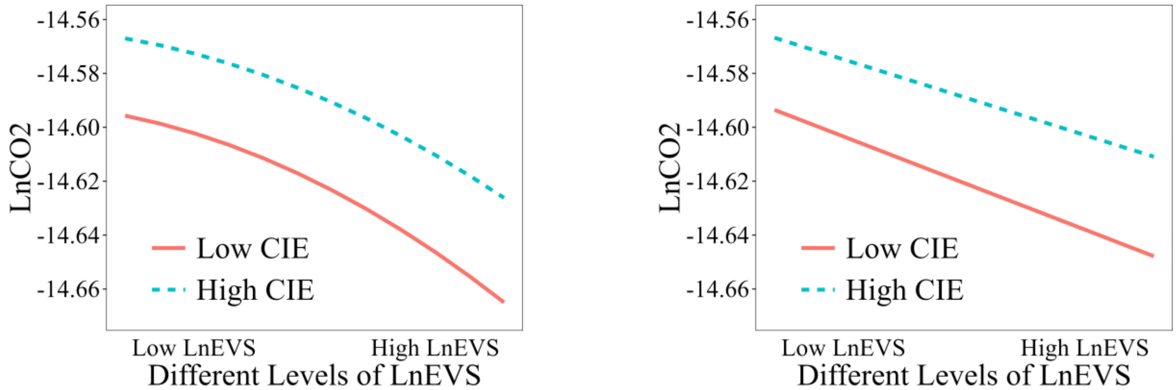
where $\tilde{X}_{it} = X_{it} - \sum_{i=1}^{N}\sum_{t=1}^{T} X_{it}/(NT)$ represents the deviation of variable X following centralization. $LnCO2_{it}$ serves as dependent variable, while $\widetilde{LnEVS}_{it}$ and its square term are independent variables. $\widetilde{CIE}_{it}$ is the moderating variable and $\widetilde{CIE}_{it}\widetilde{LnEV}_{it}$ represents the interaction term. $LnGDP_{it}$ and its square term are included as control variables. β_0, β_1, $\cdots$, β_7 are regression coefficients. Here $\mu_1 = 0$ is set to avoid dummy variables trap.

Table 8

The moderating effect of CIE on EVS and CO2.

Variable	Model (3)	Model (4)
	$LnCO2_{it}$	$LnCO2_{it}$
$\widetilde{LnEVS}_{it}$	-0.011***	-0.008**
	(0.004)	(0.003)
$\widetilde{CIE}_{it}$	1.165***	1.154***
	(0.066)	(0.068)
$\widetilde{CIE}_{it}\widetilde{LnEVS}_{it}$	0.062***	0.059***
	(0.009)	(0.007)
$\left(\widetilde{LnEVS}_{it}\right)^2$	-0.001**	/
	(0.001)	
$\widetilde{CIE}_{it}\left(\widetilde{LnEVS}_{it}\right)^2$	0.006**	/
	(0.002)	
$LnGDP_{it}$	3.073***	2.425***
	(0.739)	(0.732)
$(LnGDP_{it})^2$	-0.138***	-0.107***
	(0.034)	(0.034)
Constant	-14.607***	-11.235**
	(3.995)	(3.957)
Country FE	Yes	Yes
Year FE	Yes	Yes
Number of Obs.	222	222
Adj R^2	0.995	0.994

Table 8 encapsulates the results derived from the model. Initially, $\beta_3 > 0$ suggests that reducing the CIE level (which is indicative of an improved energy structure in power generation), can markedly lower CO2. Further, Model (3) reveals that the interaction term between CIE and EVS is significantly positive ($\beta_4 > 0$), a direction that contradicts the main effect ($\beta_1 < 0$). This suggests that enhancing the clean energy level intensifies the negative correlation between EVS and CO2. After the inclusion of the square term of EVS in Model (4), the regression coefficients for both the interaction term between CIE and EVS and its square term are significantly positive ($\beta_4, \beta_5 > 0$), insinuating the non-linear moderating role of CIE. Fig. 2 provides a more visual representation of the moderating effect of CIE based on curvilinear and linear main effects. The findings suggest that a cleaner energy structure enhances the CRE of EV, which becomes more pronounced with increased clean energy levels. Considering the non-linear relationship between EVS and CO2, this effect is amplified. Moreover, these findings lend robust support to H_2.



(a) Two-way interaction effects between a curvilinear main effect and linear moderator of CIE

(b) Two-way linear interaction effects of CIE

Fig. 2. Moderating effect plots.

4. Evaluation of CRE of EV

In this section, a model of transportation carbon emissions will be established; and through the example of 19 OECD countries, the CRE of promoting EV will be evaluated.

4.1 Carbon emissions model of EV

To assess the CRE of EV in each country, we first propose a model for estimating carbon emissions from transportation in this subsection:

$$TCE_{it} = \alpha_{it} VMT_{it} \sum_{m=1}^{M} REV_{m,it}/M + (1-\alpha_{it}) VMT_{it} \sum_{h=1}^{H} RCV_{h,it}/H, \quad (5)$$

where $i = 1,\cdots,19$ represents country, $t = 1,\cdots,11$ represents year, TCE_{it} represents the total carbon emissions (TCE) from transportation, and α_{it} stands for the stock share of EV. M and H denotes the total types of EV and CV, respectively. $REV_{m,it}$ and $RCV_{h,it}$ refer to the carbon emissions rate (the carbon emissions per vehicle mile, expressed in kg carbon dioxide per mile) of the m-th EV and the h-th CV, respectively. VMT_{it} indicates the number of vehicle miles traveled on all roads.

The REV can be obtained by multiplying the CIE by the energy efficiency, which is $\sum_{m=1}^{M} REV_{m,it}/M = \delta \times EE \times CIE_{it}$, where δ refers to the energy loss coefficient, and EE represents energy efficiency, i.e., the power consumption of EV per unit distance. Considering an average usable battery capacity of 88%, δ and EE are set as 1.136 and 0.280 kWh per mile for EV, respectively [56]. For CV, we assume that the technical level affecting their emissions remains constant and set $\sum_{h=1}^{H} RCV_{h,it}/H = 0.400$ kg carbon dioxide per mile based on previous studies [57]. Since the CRE of promoting EV disappears when it exceeds 1.250 kg-CO_2/kWh, and according to Table 2, the average CIE of OECD countries is 0.310 kg-CO_2/kWh, then we get $\sum_{m=1}^{M} REV_{m,it}/M = 0.099$ kg carbon dioxide per mile, which indirectly confirms the correctness of assumption H_1.

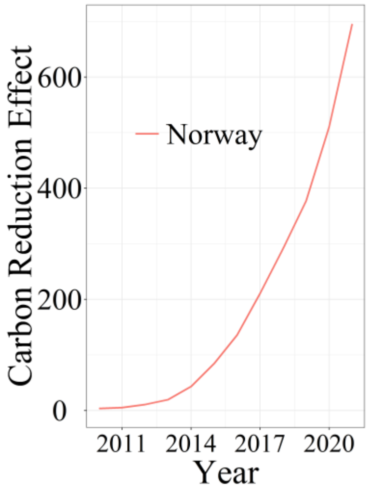
4.2 Indicator of CRE

This subsection evaluates the CRE of EV in 19 OECD countries from 2010 to 2021 based on Model (5). For missing data in VMT_{it}, the ARIMA model is employed for prediction and imputation. To assess the impact of EV on carbon emissions in a country, the first step is to estimate the carbon emissions in the absence of EV, which can be calculated in Model (5) by assuming $\alpha_{it} = 0$, denoted as TCE'_{it}. Further, TCE_{it} can be calculated by utilizing the actual α_{it} from IEA. Furthermore, due to substantial economic disparities among different countries, we use per capita terms for comparison, defining the measure of CRE of EV as the following indicator:

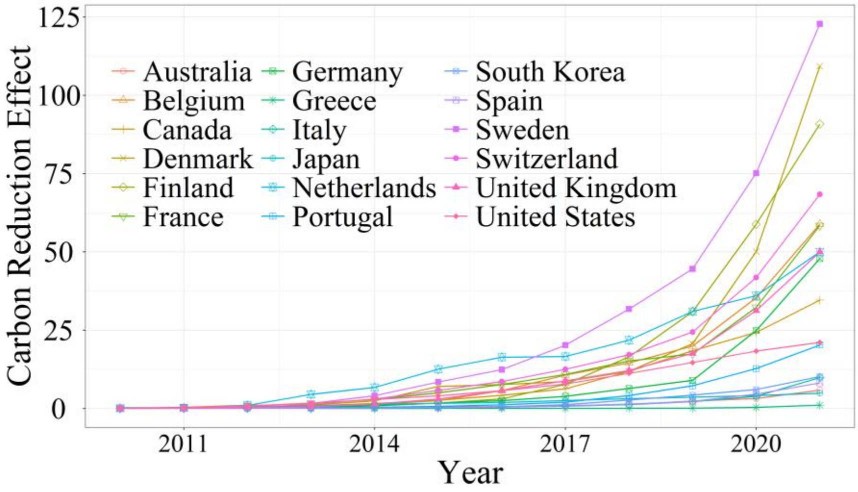
$$CRE_{it} = (TCE'_{it} - TCE_{it})/POP_{it}, \qquad (6)$$

where the unit of CRE_{it} is kg carbon dioxide per capita and POP_{it} is the population size of the t-th year.

The indicators of CRE in the 19 OECD countries from 2010 to 2021 are illustrated in Fig. 3. Although there are significant differences in the CRE among different countries, all countries show a positive CRE of EV. Moreover, there is a noticeable increase in the CRE around 2020 in all countries, likely due to the COVID-19 that reduces short-term demand for EV while stimulates long-term growth [58]. Norway, exhibiting a distinctly more outstanding CRE than other countries, is assigned a separate category. As depicted in Fig. 3(a), its CRE for 2021 is 695.766, with its EV stock share reaching 25.00% in 2021, the highest among all countries. This is primarily due to Norway's plan to ban the sale of gasoline cars starting from 2025. Moreover, Norway's CIE is only 0.026 kg-CO_2/kWh, which is also the lowest among all sample countries. All these factors have made Norway the country with the strongest CRE. Fig. 3(b) shows CRE of the remaining 18 OECD countries, with CRE ranging from 122.801 (Sweden) to 1.037 (Greece) in 2021 and EV stock share between 6.00% and 0.20%. The average CRE for all sample countries is 77.263 in 2021. It can be observed that with the gradual promotion of EV, CRE in each country increases year by year, displaying an exponential trend. To further reduce carbon emissions in the transportation sector, it is imperative to increase policy support and further lower CIE.



(a) Norway



(b) Remaining 18 OECD countries

Fig. 3. CRE of OECD countries from 2010 to 2021.

5. Conclusions

Using data from 19 OECD countries, this study primarily examines the impact of EV on carbon emissions. From a macro perspective instead of lifecycle theory, we portray the relationship between EVS and CO2 and discuss the role of energy structure. Moreover, a statistical indicator, CRE, is proposed to evaluate the influence of promoting EV. The main conclusions of this paper are as follows:

(1) The test results of econometric models based on the EKC hypothesis reveal a significant negative relationship between EVS and CO2. If solely considering the linear impact of EV sales on carbon emissions, a 1% increase in EV sales per thousand people in any given country would result in a 1.2% decrease in CO2, which is validated by robustness and

endogeneity tests.

(2) The moderating effect model indicates that a country's level of energy cleanliness significantly affects the CRE, and that the energy structure allows EV sales to have a moderate effect on carbon emissions. In other words, EV sales have a greater impact on CO2, and the CRE of EV is stronger in countries with higher energy cleanliness levels.

(3) The statistical indicator can assess the CRE of EV in various countries. The trend of the indicator shows that the gradual promotion of EV has increased CRE in all countries year by year, presenting an exponential reduction trend. Noticeably, Norway has the most substantial CRE among all studied countries. To reduce carbon emissions, countries should enhance the promotion of EV and further lower CIE.

Author contribution statement

Haoxiang Yang: Data curation, Software, Writing - original draft. **Dongping Bai:** Methodology, Software, Writing - original draft. **Guoquan Ren:** Writing - original draft. **Jun Liu**: Data curation. **Yunhao Wang:** Conceptualization, Project administration, Writing - review & editing. **Guoyu Guan:** Writing - review & editing, Funding acquisition.

Declaration of competing interest

The authors declare there are no conflict of interests.

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Appendix

Nomenclature

ARIMA: Autoregressive Integrated Moving Average
CIE: Carbon Intensity of electricity
CO2: Carbon Dioxide Emissions Per Capita
CRE: Carbon (Emissions) Reduction Effect
CV: Conventional Vehicles
EE: Energy Efficiency
EKC: Environmental Kuznets Curve
EV: Electric Vehicles
EVS: Electric Vehicles Sales Per Capita
GDP: Gross Domestic Product Per Capita
IEA: International Energy Agency
IMF: International Monetary Fund
IPCC: Intergovernmental Panel on Climate Change
LCA: Life Cycle Assessment
OECD: Organization for Economic Cooperation & Development
POP: Population
RCV: Carbon Emissions Rate of Conventional Vehicles
REV: Carbon Emissions Rate of Electric Vehicles
STO: Electric Vehicles Stock Per Capita
TCE: Total Carbon Emissions
VMT: Vehicle Miles Traveled
WMO: World Meteorological Organization

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